In search of the determinants of European asset market comovements☆

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A B S T R A C T

We show, in a broad class of affine general equilibrium models with long run risk, that the co variances between asset returns are linear functions of risk factors. We use a dynamic condi tional correlation model to measure the covariances of stock and sovereign bond markets in the Euro Area. We use a new approach to measure risk factors based on *Google* search data. The factors explain 50 to 60% of the variation of the covariances between European stocks and 25 to 35% of the covariances between European bonds. The information improves the port folio performance compared to an equally weighted portfolio.

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1. Introduction

The stylized facts that characterize the comovement of international asset markets are of great importance to economists, policymakers, and investors. These facts help economists grasp the links between the real economy and finance. They inform policymakers on how markets react to international shocks and how to design reforms of the financial system. They advise inves tors on how to improve risk management and increase their returns through the diversification of their portfolios.

Several theoretical studies have studied the comovement between asset returns. Beltratti and Shiller (1992) use a present value model to calculate the theoretical correlation between stock and bond markets. They find that the discount rate has oppo site effects on stocks and bonds. Ammer and Mei (1996) add a foreign stock return to the model and characterize the covariance between international stocks. In their application, they find that the covariance between national indexes is driven by common stock risk premia rather than by the comovement in fundamental variables. D'Addona and Kind (2006) set an affine asset pricing model and derive a formula for the stock bond correlation determined by the dynamics of inflation and the dividend yield ratio.

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Campbell, Sunderam, and Viceira (2013) consider a quadratic, rather than affine, pricing model in which the nominal term structure of interest rates is driven by the real interest rate, risk aversion, temporary and permanent components of expected inflation, and the covariance between nominal variables and the real economy. The model features a changing covariance of bond and stock returns, and helps produce negative comovements between them. Barsky (1989) builds a general equilibrium model and shows that the relationship between stocks and bonds depends on the degree of aversion, the intertemporal substitution, and the share of the corporate sector in total wealth.

We add to this literature by characterizing the asset market comovement in a recent class of affine general equilibrium models with long run risk. These models introduce small but persistent stochastic components in the mean and variance of consumption growth, which together with Epstein Zin preferences, successfully match several stylized facts in finance such as equity premium, risk free rate, market return volatility, and price dividend ratio [see Bansal and Yaron (2004)]. Our main theoretical contribution is to show that, under some general conditions, the covariance between the returns of any two assets (stocks, bonds) is a linear function of latent risk factors. Although this result is not surprising given the class of models, it has not yet been formalized in the literature. The implication for the empirical exercise is that, if measures of covariances and the risk factors are available, we can use simple linear regression techniques to predict the assets' covariance.

This result raises a challenge: both sides of the regression are unobservable. For the left hand side, we use Engle's (2002) dynamic conditional correlation (DCC) model to filter the covariances. It is common in the empirical literature to use parametric methods to filter the covariance between assets. Using correlations, filtered from a multivariate generalized autoregressive conditional heteroskedasticity (GARCH) model, between the monthly asset excess returns of seven major countries from 1960 to 1990, Longin and Solnik (1995) find that correlations increase with conditional volatility and interest rate and decrease with dividend yields. More recently, Hunter and Simon (2005) use a bivariate GARCH framework to examine the lead lag relationships and the conditional correlations between 10 year US government bond returns and their counterparts from the United Kingdom, Germany, and Japan. The DCC model that we consider has the flexibility of univariate GARCH models without the computational difficulties of multivariate GARCH models. For a robustness check, we also use nonparametric measures of covariances as in Solnik, Boucrelle, and Le Fur (1996).

For the right hand side of regression, several studies use *predetermined* variables to explain the comovement between asset returns. For example, von Furstenberg and Jeon (1989) use interest rate differentials, exchange rates, and prices of oil and gold. Campbell and Ammer (1993) use dividends, inflation, short term real interest rates, and excess stock and bond returns. D'Addona and Kind (2006) and Beltratti and Shiller (1992) use inflation and the dividend yield ratio. Alternatively, other studies use econometric factor models to extract the latent variables. King, Sentana, and Wadhwani (1994) use 16 national stock markets and a multivariate factor model in which the volatility of returns is induced by changing volatility in the orthogonal factors. They find that only a small proportion of the time variation in the covariances between national stock markets can be accounted for by observable economic variables. Baele, Bekaert, and Inghelbrecht (2010) use a dynamic factor model in which the coefficients depend on sudden regime changes. They find that macroeconomic fundamentals contribute little to explaining stock and bond return correlations whereas other factors, especially liquidity proxies, play a more important role. We follow this latter literature that uses factor analysis and we extract a number of factors from a large set of data using principal component analysis.

The empirical literature also differs on the frequency of the data. Studies focusing on financial variables generally use weekly data, such as in Clare and Lekkos (2000) and Solnik et al. (1996), or daily data, such as in von Furstenberg and Jeon (1989). In general, studies that focus on economic determinants use yearly, as in Beltratti and Shiller (1992), quarterly as in Baele et al. (2010) and Campbell et al. (2013), or monthly data, such as in Campbell and Ammer (1993). The literature has found two ways to address the clear mismatch between the frequency of financial and economic data. On the one hand, there are event studies, such as that by Karolyi and Stulz (1996), which investigate how US macroeconomic announcements affect the correlation between Japanese and US stocks using daily data from 1988 to 1992. Other researchers have used Mixed data sampling methods (MIDAS), as in Ghysels, Santa Clara, and Valkanov (2006); Ghysels, Sinko, and Valkanov (2007). One example is Engle, Ghysels, and Sohn (2013) that analyzes the relation between stock market volatility and macroeconomic activity since the 19th century, distinguishing short run from secular movements. They use the MIDAS approach to link the monthly, quarterly, or bi annual macroeconomic variables to the secular component and a mean reverting daily GARCH process for the short run movements. They find that at a daily level, inflation and industrial production growth, account for between 10% and 35% of one day ahead volatility prediction.

Our second main contribution is to use a novel type of data based on *Google* keyword searches to address the mismatch of the frequency of economic and financial data. *Google* designed an application, *Google Trends*, which provides indexes of how many times people have “Googled” a specific word or combination of words relative to overall traffic. These indexes have been available at a weekly frequency since 2004 for individual countries.

Choi and Varian (2012) were the first to claim that *Google Trends* data predict several aspects of the current economic activity. Since then, researchers have used these data to forecast labor markets, housing markets, automobile sector, inflation expectations, or private consumption. Askitas and Zimmermann (2009); D'Amuri (2009); D'Amuri and Marcucci (2010), and Choi and Varian (2009) demonstrate the power of internet job search indicators to predict unemployment rate or the initial claims of unemployment benefits in the United States and Germany. Vosen and Schmidt (2011) construct an indicator for private consumption and claim that it is superior to the common survey based indicators such as the University of Michigan Consumer Sentiment Index. Similar results were reported in Della Penna and Huang (2009) and Kholodilin, Podstawski, and Siliverstovs (2010). Guzman (2010) proposes a measure of real time inflation expectations based on *Google* search data, comparing it with 37 indicators of inflation expectations. The indicator anticipates the inflation rate by 12 months and has the lowest forecast error. Wu and

Brynjolfsson (2013) find that a housing search index predicts future housing market sales and prices; central banks also use these data. McLaren and Shanbhogue (2011) predict changes in unemployment rate and housing prices in the United Kingdom. Carrière Swallow and Labbé (2013) find that the internet search index of automobiles improves the fit of models of automobile sales in Chile. Suhoy (2009) improves the unemployment forecast in Israel. In other fields, internet search data has been used to detect influenza epidemics [Ginsberg et al. (2009)].

These data are available at a weekly frequency for different countries, which provides possible applications to the finance lit erature. Da, Engelberg, and Gao (2011) were the first to do so. They use the keyword search of the code name of specific stocks to construct a measure of investor attention, which is correlated with other proxies of investor attention but is available in a more timely fashion. They find that increases in the measure predict higher stock prices in the following two weeks and an eventual price reversal within the year. Latoeiro, Ramos, and Veiga (2013) use a similar strategy to predict stock market activity of European stocks. They find that an increase in the searches for stocks is followed by a temporary increase in volatility and volume and a drop in cumulative returns.

Our contribution is to link these two strands of the literature. As the *Google* search indicators relate to economic fundamentals but are available at a weekly frequency, we can connect them to certain properties of financial markets. We can explore the data comparability across countries and avoid the use of economic data, which are only available with time lags at a quarterly or monthly frequency.

In the empirical application, we predict the covariances between asset returns in four Euro Area countries: Germany, France, Italy, and Spain. We analyze the stock and sovereign bond markets, before and during the Eurozone crisis, when the variation in market covariances became more pronounced. While this sample is of great interest for economists and policymakers, few studies focus on it. Perego and Vermeulen (2013) study the macroeconomic determinants of European stock and bond market correla tions between 1999 and 2012. Tamakoshi, Toyoshima, and Hamori (2012) focus on the correlation of Greek stock market returns with those of six other Euro Area countries during the crisis. Kenourgios and Samitas (2009) study the correlation of both equity and bond markets of Euro Area and new accession countries, on the decade prior to the crisis.

We use the DCC model to filter the weekly covariances in the Euro Area. We select 10 indicators from *Google Trends* related with economic activity for the United States and the four European countries. For each country, we extract a number of factors with principal component analysis. These factors are correlated with several monthly macroeconomic indicators for all countries, particularly with changes in unemployment rate, inflation, or the growth rate of industrial production. All factors exhibit a clear cyclical pattern. We consider the US factors as global and the orthogonalized European ones as country specific. We regress the different measures of covariance on these factors.

The factors extracted from *Google* search data predict the comovement in cross country European stock and sovereign bond markets. They explain 50 to 60% of the variation of the covariance of stock market returns and 25 to 35% of the variation of bond market returns. While the comovement of European stock markets is mainly due to global factors, the country specific ones are more important in the dynamics of the sovereign bond market. In all regressions, a deterioration of economic activity in the United States raises the covariance within European bond and stock markets. Furthermore, we find that the comovement between stock and bond returns within the same European country is again dominated by the global factors. Interestingly and as opposed to the results obtained for cross country stock and bond comovements, it seems that all the different dimensions of a US recession decrease the covariance between stock and bond markets of same European country.

Our third and final contribution is to measure the financial gains for investors of using the information in *Google* search data. The aforementioned literature does not evaluate how the determinants of the comovement of assets can improve portfolio diver sification. One notable exception is the study by Ang and Bekaert (2002), which sets up a general asset allocation problem with regime switching capturing asymmetric correlation. They evaluate the financial gains of considering asymmetric correlation be tween international equities instead of a symmetric one. We use a portfolio selection approach to examine the implications of time varying covariances between international stock and bond returns for asset allocation and risk management. Following Brandt, Santa Clara, and Valkanov (2009) and Bouaddi and Taamouti (2013), our approach consists of directly modeling portfolio weights as a function of the global factors. The empirical results indicate that most of the global factors have a statistically signif icant effect on portfolio weights. Furthermore, the portfolio with time varying weights outperforms an equally weighted portfolio or a portfolio with constant weights, in mean returns and Sharpe ratios, both in and out of sample. Part of the gains is due to the weekly frequency of the portfolio adjustment.

The rest of the paper is organized as follows. Section 2 provides the theoretical model underpinning the asset returns' comovement. Section 3 describes the data and measures of covariances between asset returns, extracts the risk factors using *Goo gle* search data, and shows their correlation with economic activity. Sections 4 and 5 report how the covariances depend on the global and country specific factors. Section 6 examines the implications for international portfolio allocation and risk manage ment. Section 7 presents the conclusions. Proofs and additional results appear in Online Appendices A to E.

2. The theoretical relationship between international asset market returns

This section motivates the empirical analysis performed in the paper. In particular, we provide a justification for the use of lin ear regression models to explain the international asset market comovements as an affine function of the variables underlying the state of the economy (hereafter state variables). We show that this affine relationship between the state variables and the covari ance between international asset returns is an implication of the affine general equilibrium models described in Duffie, Pan, and Singleton (2000); Eraker (2008), and Feunou, Taamouti, and Tedongap (2014). These models can be interpreted in terms of long run risk models introduced by Bansal and Yaron (2004) and match several stylized facts in finance. Focusing on two countries, Colacito and Croce (2010, 2013) have recently consider similar type of models to show the welfare gains of financial integration that are related to risk sharing, and to document that both the anomaly of low correlation between consumption differentials and exchange rates, and the forward premium anomaly, have become more severe over time.

Let us denote $r^{a_1}_{t+1}=(r^{a_1}_{t+1,1},\ldots,r^{a_1}_{t+1,n})^T$ and $r^{a_2}_{t+1}=(r^{a_2}_{t+1,1},\ldots,r^{a_2}_{t+1,n})^T$ as the vectors of asset returns a_1 and a_2 in n countries, respectively. Asset returns a_1 and a_2 could be given by equity and/or bond returns. We consider an economy with K state vari ables, X_t, and with the following properties: (i) the joint distribution of $(r^{a_1}_{t+1},r^{a_2}_{t+1})$ and X_t belongs to the family of affine jump diffusion continuous time (or discretized) models (Duffie et al., 2000); and (ii) the stochastic discount factor is an exponential affine function of X_t and $(r^{a_1}_{t+1},r^{a_2}_{t+1})$ (Gourieroux and Monfort, 2007; Christoffersen et al., 2010). Feunou et al. (2014) formalize these properties and show that this class of models nests a wide array of discrete time asset pricing models. Indeed, the affine long run risk models with Epstein Zin Weil preferences (Bansal & Yaron, 2004; Eraker, 2008) also fit this description.

In the context of the above class of models, we show (see Appendix A) that the covariance between the vectors of internation al asset returns (equity and/or bonds), $r^{a_1}_{t+1}$ and $r^{a_2}_{t+1}$, is given by:

$$E_t\left[r^{a_1}_{t+1}\left(r^{a_2}_{t+1}\right)^T\right] \quad \beta_{a_1,a_2,0}+X_t^T\otimes\beta_{a_1,a_2,X}, \tag{1}$$

where "⊗" is the Kronecker product, and $\beta_{a_1,a2,0}$ and $\beta_{a_1,a2,X}$ are the intercept and slope coefficients. Eq. (1) states that the covari ance between any two assets is given by a linear function of the state variables X_t. This result motivates the specification used in Section 4. One limitation of this approach is that it does not provide a direct link between the unobserved state variables and spe cific economic variables. While some people associate them with predetermined variables such as unemployment rate or inflation, we opt to extract them from a large set of data.

3. Data description

3.1. Stock and bond market returns and covariances

Our empirical analysis covers four European countries (France, Germany, Italy, and Spain) along with the United States. The weekly dataset runs from January 2002 to October 2011. Data for the sovereign bond yields, which is for the 10 year government bond end of day data are obtained from Reuters, and the stock market data is obtained from an equity index reported in Datastream.

We define the weekly stock market return $r^s_{i,t}$ at week t for country i as the difference in log prices of the equity index on the Friday from the previous week, and we define the bond market return $r^b_{i,t}$ as the difference in log yield at the previous Friday from the following week. We use two different approaches to measure the ex post time varying covariances between international stock and bond returns: **(i)** the DCC model and **(ii)** a nonparametric approach by computing a rolling pairwise covariance of weekly returns.

Proposed by Engle (2002) to capture the dynamics in correlation, the DCC model is becoming a benchmark model for multi variate specifications. The DCC has the flexibility of univariate GARCH models, but it still provides parsimonious correlation spec ifications without the computational difficulties of multivariate GARCH models. Further, this model allows for the conditional correlations (covariances) to evolve according to a GARCH type structure. In these, the number of parameters in the conditional correlation model can be limited by using the idea of "correlation targeting", which means that the unconditional correlations im plied by the model are restricted to be equal to the unconditional sample correlations. For a bivariate process, the GARCH(1,1) type specification of conditional correlation coefficient between the return of an asset in country i and the return of another asset in country j, say $\rho_{i,j,t+1}$, is given by

$$\rho_{i,j,t+1} \quad Corr\left(r_{i,t+1},r_{j,t+1}\right) \quad \frac{q_{ij,t+1}}{\sqrt{q_{ii,t+1}q_{jj,t+1}}}, \tag{2}$$

where the auxiliary variable $q_{ij,t+1}$ is defined by

$$q_{ij,t+1} \quad \overline{\rho}_{ij}+\lambda_1\left(z_{i,t}z_{j,t}-\overline{\rho}_{ij}\right)+\lambda_2\left(q_{ij,t}-\overline{\rho}_{ij}\right), \tag{3}$$

and in turn, where $z_{i,t}$ and $z_{j,t}$ are the normalized return innovations, and $\overline{\rho}_{ij}$ is the unconditional expectation of the cross product of return innovations between the asset return in country i and that in country j. While $q_{ij,t+1}$ is not explicitly the covariance, it can be interpreted as the covariance dynamics.

Appendix B.1 reports the estimated coefficients of the GARCH model and the DCC model in Eq. (3). The GARCH coefficient es timates are positive and statistically significant for both stock and bond returns across the different pairs of countries. The high values (close to one) of the GARCH coefficient estimates indicate that volatilities are persistent. The estimated coefficients of the DCC model, λ_1 and λ_2, are positive for stocks and bonds across all countries. The estimates of λ_1 are statistically significant in most of the cases, whereas the estimates of λ_2 are always significant. The high values of λ_2 indicate a high persistence in cor relation. The graphs of the estimated dynamic covariances and correlations can be found in Appendix B.2.

We also estimate nonparametrically the covariances between any two assets. We use an arithmetic equally weighted estimator (hereafter moving average estimator). For a sample of returns $\{r_{i,t}, r_{j,t}\}_{t\ \ 1}^{T}$, the moving average estimator of covariances between the returns in country i and in country j, say $q_{ij,t+1}$, is given by the following formula:

$$q_{ij,t+1} \quad \frac{1}{m}\sum_{\tau\ \ t\ \ m}^{t}\left(r_{i,\tau}-\overline{r}_{i,t+1}\right)\left(r_{j,\tau}-\overline{r}_{j,t+1}\right) \tag{4}$$

where

$$\overline{r}_{h,t+1} \quad \frac{1}{m}\sum_{\tau\ \ t\ \ m}^{t} r_{h,\tau}, \text{for } h \quad i,j.$$

In the empirical application, we take $m=20$ weeks. Furthermore, the nonparametric estimator of correlations between two assets, say $\rho_{ij,t+1}$, is given by the following formula:

$$\rho_{ij,t+1} \quad \frac{\sum_{\tau\ \ t\ \ m}^{i}\left(r_{i,\tau}-\overline{r}_{i,t+1}\right)\left(r_{j,\tau}-\overline{r}_{i,t+1}\right)}{\sqrt{\left(\sum_{\tau\ \ t\ \ m}^{i}\left(r_{i,\tau}-\overline{r}_{i,t+1}\right)^{2}\right)\left(\sum_{\tau\ \ t\ \ m}^{t}\left(r_{j,\tau}-\overline{r}_{j,t+1}\right)^{2}\right)}}. \tag{5}$$

3.2. Measurement of international risk factors: Google Trends

To extract the international risk factors, we use a novel type of data based on internet keyword search, provided by *Google Trends*. The data consist of indexes that reflect how many times people have "Googled" a specific word or combination of words, relative to overall traffic. These indexes are available at a weekly frequency since 2004 by country. Usually, the data is available up to the previous week. *Google Trends* also provides compound indexes of specific categories. As explained in the intro duction, several studies have shown that these indexes are good predictors of key economic indicators such as unemployment rate, private consumption, or real time inflation expectations.

The data from *Google Trends*, which are available at a weekly frequency, enables the connection between economic and finan cial data. In reality, the joint movement of stock and sovereign bond markets is driven by macroeconomic factors: unemployment, investment, private consumption, inflation, government spending, taxation, and so forth. These data are only available at a quar terly frequency or, for some variables, at a monthly frequency. To use them, one must average the financial data and lose a significant fraction of their variation. The use of the internet search data that are correlated to the evolution of macroeconomic aggregates allows us to overcome this obstacle.

To extract the factors, we proceed in the following way. First, for each of the countries under consideration, we get 10 indexes related to several dimensions of economic activity: *economic news, jobs, fiscal policy news, credit and lending, manufacturing, industrial materials equipment, construction and maintenance, property, currency and foreign exchange, and automobile industry.*

Table 1
Selected factors and main components.

Country	Factor	Main components
United States	f_1^{us} (0.38)	Jobs (0.68), economic news (0.61), currency & foreign exchange (0.56)
	f_2^{us} (0.23)	Property (0.71), construction (0.56), lending & credit (0.37)
	f_3^{us} (0.11)	Manufacturing (0.41), lending & credit (0.25), industrial materials & equipment (0.21)
Germany	f_1^{de} (0.55)	Construction (0.48), lending & credit (0.42), jobs (0.42)
	f_2^{de} (0.18)	Currency & foreign exchange (0.61), fiscal policy news (0.32), construction (0.13)
France	f_1^{fr} (0.50)	Construction (0.60), industrial materials & equipment (0.42), economy news (0.25)
	f_2^{fr} (0.17)	Lending & credit (0.45), property (0.37), currency & foreign exchange (0.22)
	f_3^{fr} (0.11)	Currency & foreign exchange (0.45), economy news (0.20), property (0.08)
Italy	f_1^{it} (0.39)	Lending & credit (0.27), jobs (0.13), property (0.11)
	f_2^{it} (0.16)	Fiscal policy news (0.22), currency & foreign exchange (0.21), property (0.03)
	f_3^{it} (0.12)	Economy news (0.34), automobile industry (0.11), currency & foreign exchange (0.11)
Spain	f_1^{sp} (0.33)	Lending & credit (0.30), fiscal policy news (0.30), currency & foreign exchange (0.18)
	f_2^{sp} (0.21)	Property (0.30), automobile industry (0.29), economy news (0.14)
	f_3^{sp} (0.19)	Currency & foreign exchange (0.54), fiscal policy news (0.17), lending & credit (0.09)

Note: This table reports the factors extracted with principal component analysis using 10 indexes of economic activity: economic news, jobs, fiscal policy news, credit and lending, manufacturing, industrial materials and equipment, construction and maintenance, property, currency and foreign exchange, and automobile industry. For each country, the factors with an eigenvalue greater than 1 are selected. In the second column, in parentheses, is the proportion of the overall variance explained by each of the factors. The third column shows the three indexes with the highest R-squared of the marginal regressions, with the respective R-squared in parentheses. The sample consists of 469 observations from 2004w1 to 2012w51. The Kaiser–Meyer–Olkin measure of sampling adequacy is 0.81 for the United States, 0.90 for Germany, 0.87 for France, 0.92 for Italy, and 0.84 for Spain.

These indexes are constructed based on searches of related words. Appendix C.1 shows the most important keywords for each index in each country. The indexes are available since the first week of 2004. There are strong elements of seasonality that we removed using a ratio to moving average method. We use the indexes in logs. An augmented Dickey Fuller test for unit root in dicates that the indexes are stationary around a deterministic trend, so we remove it to get a stationary time series. Thereafter, for each country, we carry out principal component analysis and extract the factors associated with eigenvalues greater than 1. They are considered practically significant because they explain an important amount of the variability in the data, while those with eigenvalues less than 1 are practically insignificant. Appendix C.2 shows the 10 indexes for the United States and the extracted factors for all countries.

Table 1 summarizes the number of selected factors and the percentage of the variance explained. The selected factors (eigen values greater than 1) explain more than two thirds of the variability of the data in all countries. Following Ludvigson and Ng (2009), we quantify the relationship between the estimated factors and the original indexes using the coefficient of determination in regression analysis. In the third column of Table 1, the three indexes with the highest R squared of the marginal regressions are shown, with the R squared in parentheses.

For the United States, we can interpret the first factor as related to jobs and general economic activity, the second related to construction and property, and the third related to manufacturing and investment. For the European countries, we interpret the first factor as a general economic performance. We interpret the second factor of Germany and Italy and the third factor of Spain and France as related to the Eurozone crisis because it involves generally the indexes of *fiscal policy news*, *currency and foreign exchange*, and other indexes related to credit or construction.

We treat the US factors as global and the European country factors as country specific. To make sure that the specific factors do not contain redundant information, we regress them on the three US factors:

$$f^i_{l,t} \quad \alpha_0 + \alpha_1 f^{us}_{1,t} + \alpha_2 f^{us}_{2,t} + \alpha_3 f^{us}_{3,t} + \mu_t, \tag{6}$$

for any factor l of country i. We then use the residuals from each regression as specific factors that are orthogonal to the global factors, defining them as $\hat{f}^i_{l,t}$. The estimation results are reported in Appendix C.3. The country specific factors share a lot of information with the US factors, with an average R squared of 0.43. The regression coefficients are statistically significant at the 1 percent level in most cases. In the application, the global factors together with the orthogonalized specific factors are used to explain the European stock and bond comovements.

Table 2
Google factors and monthly economic activity.

Variable	f^i_1		f^i_2		f^i_3		R^2	Obs
United States								
Unemployment rate	0.041	(4.44)**	0.023	(2.12)*	0.059	(4.05)**	0.37	107
Consumer price index	0.001	(2.10)*	0.000	(0.90)	0.000	(0.47)	0.07	107
Industrial production	0.002	(3.93)**	0.000	(0.21)	0.002	(3.17)**	0.26	107
Germany								
Unemployment rate	0.021	(4.94)**	0.028	(4.28)**			0.30	107
Consumer price index	0.072	(3.91)**	0.018	(0.64)			0.13	107
Industrial production	0.118	(1.40)	0.394	(2.99)**			0.10	107
France								
Unemployment rate	0.008	(1.36)	0.025	(2.62)**	0.024	(2.08)*	0.12	107
Consumer price index	0.032	(2.04)*	0.042	(1.53)	0.046	(1.37)	0.07	107
Industrial production	0.015	(0.02)	0.097	(0.67)	0.351	(1.99)*	0.04	107
Italy								
Unemployment rate	0.017	(1.21)	0.009	(0.47)	0.023	(1.02)	0.03	107
Consumer price index	0.063	(1.30)	0.057	(0.84)	0.061	(0.72)	0.03	107
Industrial production	0.277	(2.59)*	0.373	(2.48)*	0.171	(0.92)	0.13	107
Spain								
Unemployment rate	0.068	(5.07)**	0.016	(1.15)	0.103	(6.97)**	0.46	107
Consumer price index	0.099	(1.91)	0.035	(0.68)	0.011	(0.19)	0.04	107
Industrial production	0.337	(2.53)*	0.071	(0.53)	0.240	(1.75)	0.10	107

Note: This table reports the estimation results of the regression of each economic indicator on all the extracted factors of the respective country. The weekly factors are averaged for the month. Unemployment rate is in first differences, while consumer price index and industrial production index are in growth rates. The sample consists of 107 observations from 2004m1 to 2012m11. In parentheses are the t-statistic of the coefficient.

** Means significant at 1%.

* Means significant at 5%.

3.3. Google Trends based factors and economic activity

Having constructed the factors, we investigate whether they are correlated with macroeconomic fundamentals. We carry out the analysis with three key monthly series: unemployment rate, consumer price index, and industrial production index. We first compute the monthly average of the factors. For each country, we regress each of the economic variables on the corresponding factors. To make the variables stationary, we include unemployment rate in first differences and consumer price index and indus trial production index in growth rates. Table 2 shows the results.

For all countries, the estimated factors have a statistically significant correlation with at least one economic variable. In all cases, the factors are negatively correlated with economic activity, either in the form of higher changes in unemployment, lower industrial production growth or lower inflation rate. The estimated factors are identified up to a sign change, but this association with economic activity, will allow an economic interpretation of the sign of the coefficients in the regressions in the following section. We repeat the exercise with the orthogonalized factors. The sign of the relationship is the same for all factors with the exception of the third factor of France (Appendix C.4).

We carry out a further robustness exercise for the United States. We retrieve 25 weekly and monthly economic series from the St. Louis FED Federal Reserve Economic Data, divided in the following categories: labor market, industrial production, housing market, trade, prices, and income. For most of the considered variables, we do not reject the null of unit root, so we make the variables stationary by taking the first differences. The description of the variables and the correlation with the factors are presented in Appendix C.4. The sign of the regression coefficient confirms that the US factors are negatively related to economic activity. The test statistics indicate that most of the economic fundamentals under consideration are related with the first and third factors but less so with the second factor. The R squared is 0.2 on average for the 25 series.

4. Empirical results

4.1. Predicting cross country stock and bond comovements

We run the following regression:

$$Cov_{t+1}\left(r^k_{i,t+1}, r^k_{j,t+1}\right) \quad \nu + \phi' \mathbf{f}^{us}_t + \lambda' \hat{\mathbf{f}}^i_t + \pi' \hat{\mathbf{f}}^j_t + \varepsilon_{t+1}, \tag{7}$$

where $Cov_{t+1}(r^k_{i,t+1}, r^k_{j,t+1})$ is the covariance between asset returns in countries i and j, for $k=$ stock return, bond return; $\mathbf{f}^{us}_t$ is the vector of global factors; and $\hat{\mathbf{f}}^i_t$ and $\hat{\mathbf{f}}^j_t$ are the vectors of specific factors of countries i and j, respectively. The estimation results are presented in Tables 3 and 4. Robust standard errors are used.

Table 3
Cross-country stock market returns covariance.

	DE–FR	DE–IT	DE–SP	FR–IT	FR–SP	IT–SP
Global						
f^{us}_2	0.341 (8.98)**	0.349 (8.85)**	0.353 (7.76)**	0.315 (9.48)**	0.329 (8.29)**	0.308 (8.99)**
f^{us}_2	0.281 (7.21)**	0.325 (8.29)**	0.306 (6.95)**	0.302 (9.38)**	0.320 (8.03)**	0.337 (10.68)**
f^{us}_3	0.365 (7.08)**	0.369 (6.86)**	0.371 (6.37)**	0.311 (6.79)**	0.339 (6.26)**	0.292 (6.26)**
Country-specific						
$\hat{f}^{de}_1$	0.095 (2.50)*	0.035 (0.97)	0.088 (2.12)*			
$\hat{f}^{de}_2$	0.249 (3.29)**	0.298 (3.62)**	0.171 (1.94)			
$\hat{f}^{fr}_1$	0.084 (2.37)*			0.077 (2.99)**	0.031 (0.89)	
$\hat{f}^{fr}_2$	0.021 (0.49)			0.053 (1.34)	0.038 (0.82)	
$\hat{f}^{fr}_3$	0.130 (2.37)*			0.013 (0.24)	0.034 (0.57)	
$\hat{f}^{it}_1$		0.022 (0.46)		0.048 (1.25)		0.044 (1.01)
$\hat{f}^{it}_2$		0.012 (0.25)		0.039 (0.83)		0.008 (0.14)
$\hat{f}^{it}_3$		0.031 (0.80)		0.019 (0.52)		0.019 (0.53)
$\hat{f}^{sp}_1$			0.019 (0.44)		0.037 (0.88)	0.040 (0.96)
$\hat{f}^{sp}_2$			0.081 (1.87)		0.050 (0.96)	0.069 (1.70)
$\hat{f}^{sp}_3$			0.160 (1.82)		0.144 (2.04)*	0.161 (2.24)*
R^2	0.602 [0.571]	0.598 [0.572]	0.572 [0.547]	0.596 [0.585]	0.565 [0.550]	0.573 [0.556]
Obs	408	408	408	408	408	408

Note: This table reports the estimation results of the regression of the covariance of stock market returns in two countries on the global and orthogonalized country-specific factors [see Eq. (7)]. The coefficients reported were multiplied by 10^3 for readability. The sample consists of 408 observations from 2004w1 to 2011w45. In parentheses are the t-statistic of the coefficient using robust standard errors. In brackets are the R-squared of the regression with only global factors.
** Means significant at 1%.
* Means significant at 5%.

Table 4
Cross-covariance.

	DE–FR	DE–IT	DE–SP	FR–IT	FR–SP	IT–SP
Global						
f_2^{us}	0.120 (6.83)**	0.083 (5.89)**	0.140 (7.43)**	0.008 (1.17)	0.076 (7.42)**	0.034 (2.01)*
f_2^{us}	0.186 (9.93)**	0.012 (0.55)	0.044 (1.64)	0.069 (7.82)**	0.046 (3.29)**	0.113 (4.49)**
f_3^{us}	0.116 (4.47)**	0.094 (3.40)**	0.164 (4.82)**	0.030 (2.75)**	0.083 (4.08)**	0.036 (0.90)
Country-specific						
$\hat{f}_1^{de}$	0.050 (1.84)	0.013 (0.55)	0.054 (1.99)*			
$\hat{f}_2^{de}$	0.090 (2.11)*	0.051 (1.15)	0.171 (2.82)**			
$\hat{f}_1^{fr}$	0.010 (0.74)			0.0378 (3.71)**	0.057 (2.23)*	
$\hat{f}_2^{fr}$	0.032 (1.01)			0.322 (2.02)*	0.071 (1.60)	
$\hat{f}_3^{fr}$	0.083 (2.26)*			0.066 (3.48)**	0.141 (2.77)**	
$\hat{f}_1^{it}$		0.014 (0.43)		0.007 (0.67)		0.127 (1.27)
$\hat{f}_2^{it}$		0.170 (4.27)**		0.047 (2.49)*		0.044 (0.52)
$\hat{f}_3^{it}$		0.140 (3.18)**		0.057 (4.00)**		0.346 (2.95)**
$\hat{f}_1^{sp}$			0.101 (2.01)*		0.014 (0.55)	0.100 (2.44)*
$\hat{f}_2^{sp}$			0.073 (3.53)**		0.013 (0.30)	0.060 (0.80)
$\hat{f}_3^{sp}$			0.612 (1.31)		0.013 (0.30)	0.013 (0.13)
R^2	0.356 [0.336]	0.253 [0.127]	0.282 [0.239]	0.279 [0.215]	0.270 [0.194]	0.236 [0.049]
Obs	408	408	408	408	408	408

Note: This table reports the estimation results of the regression of the covariance of bond market returns in two countries on the global and orthogonalized country-specific factors [see Eq. (7)]. The coefficients reported were multiplied by 10^3 for readability. The sample consists of 408 observations from 2004w1 to 2011w45. In parentheses are the t-statistic of the coefficient using robust standard errors. In brackets are the R-squared of the regression with only global factors.
** Means significant at 1%.
* Means significant at 5%.

Table 3 shows that the global factors are the main determinants of international stock comovements; they are statistically significant at the 1 percent level for all country pairs. All global factors have a positive impact on the covariance between European stock returns. Given the relationship of the factors with economic activity [see Table 2], all the different dimensions of a US recession increase the co variance in European stock markets. The R squared of each regression is between 0.57 and 0.60 and remains high if we exclude the spe cific factors (between 0.55 and 0.57). Still, some are statistically significant. A worsening of economic activity in Germany increases the covariance between the stock market returns of all other European countries. The third factor from Spain also has a positive effect on the covariance. As for France, there are mixed effects, and for Italy, none of the specific factors are significant.

For the bond market, the results are somewhat different [see Table 4]. First, all factors explain less variation than for the stock market. The R squared varies only between 0.23 and 0.35. Also, the specific factors are relatively more important. When we ex clude them, the R squared falls from an average of 0.28 to 0.19. This is particularly visible in the covariances with Italian and Spanish bond returns.

Similarly to the stock market returns, the US global factors have a statistically significant impact on the covariances between European bond returns. The first and third global factors positively affect the covariances. The second factor has more mixed ef fects, with a positive sign in four cases and a negative, statistically significant effect in only one case. Overall, if we combine the signs of the coefficients of the impact of Google search based factors on key economic variables [see Table 2] with those of the impact of the factors on the cross country bond returns covariance [see Table 4], we conclude that a worsening of the US econom ic activity raises the covariance between European sovereign bond returns.

The specific factors contribute to the comovements in the European bond markets. However, the sign of their effects changes depending on the pairs of countries. A deterioration of economic activity in Germany raises the covariance with France but lowers it with Spain. For Italy, worsening activity lowers the covariance with France but raises it with Spain. Also, the Spanish first factor raises the covariance with Germany but lowers it with Italy.

4.2. Predicting within country stock and bond comovements

4.2.1. Predicting covariances

We look at the comovement between stock and bond returns within a country. In particular, we estimate the following regression:

$$Cov_{t+1}\left(r_{i,t+1}^{s}, r_{i,t+1}^{b}\right) \quad \nu + \phi' \mathbf{f}_t^{us} + \lambda' \hat{\mathbf{f}}_t^{i} + \varepsilon_{t+1}, \tag{8}$$

where $Cov_{t+1}(r_{i,t+1}^{s}, r_{i,t+1}^{b})$ is the covariance between stock and bond returns in country i and f_t^{us} and $\hat{f}_t^{i}$ are the vectors of global factors and specific factors of country i, respectively. The results using parametric measures of covariance are provided in Table 5.

Table 5 shows that the covariances between stock and bond returns of the same European country are again driven by the global factors. All global factors have negative and statistically significant effects, with the exception of the second global factor that has a positive sign in the case of Germany and France. Thus, generally if we combine the signs of the coefficients with those in Table 5, as opposed to the results obtained for cross country comovement, it seems that all the different dimensions of a US recession decrease the covariance between stock and bond markets of same European country. The country specific fac tors only seem relevant for the comovements between stock and bond returns in Italy, as the R squared drops from 0.23 to 0.08 when we exclude them.

4.2.2. Predicting variances

Although the main focus of this paper is on explaining the time series of international market comovements measured by the covariances between international asset returns, in this subsection we consider implications for the second moments of the asset returns and investigate the main determinants of their volatilities. In particular, we consider the following regression:

$$Var_{t+1}\left(r^{k}_{i,t+1}\right) \quad \nu + \phi' \mathbf{f}^{us}_{t} + \lambda' \hat{\mathbf{f}}^{i}_{t} + \varepsilon_{t+1}, \tag{9}$$

where $Var_{t+1}(r^{k}_{i,t+1})$ is the variance of the return in country i, for $k=$ stock return, bond return; f^{us}_{t} is the vector of global factors; and $\hat{f}^{i}_{t}$ is the vector of specific factors of country i, respectively. The estimation results are presented in Tables 6 and 7. Robust standard errors are used.

Table 6 summarizes the results of the impact of global and country specific factors on the volatilities of European stock returns. From this and as for the covariances in the previous section, we see that the global factors are the main determinants of European stock comovements. Their effects are positive for all countries under consideration and they are statistically significant at the 1 percent level. Implying that the different dimensions of a US recession increase the volatility in European stock markets. The R squared of each regression is between 0.54 and 0.57 and remains high if we exclude the specific factors (between 0.52 and 0.57). The sign and statistical significance of the impact of country specific factors is unstable and changes depending on the countries, except for Germany.

For the bond market, the results are somewhat different [see Table 7]. Although the sign of the impact of global factors re mains positive, its statistical significance is less important compared to the results obtained for stock market, in particular for Italy and Spain. Moreover, the sign and statistical significance of the impact of country specific factors is unstable and changes depending on the country, except for Germany. Overall, all factors explain less variation than for the stock market. The R squared varies only between 0.11 and 0.26, or between 0.05 and 0.24 when we exclude the specific factors. The latter numbers indicate that the specific factors are relatively more important for explaining the bond market volatility.

Table 5
Stock and bond market returns covariance (using DCC model).

	Germany	France	Italy	Spain
Global				
f^{us}_1	0.058 (6.37)**	0.051 (11.32)**	0.011 (1.72)	0.018 (2.45)*
f^{us}_2	0.113 (9.42)**	0.055 (9.42)**	0.038 (4.37)**	0.020 (2.24)*
f^{us}_3	0.051 (3.38)**	0.051 (6.85)**	0.031 (2.86)**	0.040 (3.51)**
Country				
$\hat{f}^{de}_1$	0.014 (1.27)			
$\hat{f}^{de}_2$	0.082 (3.37)**			
$\hat{f}^{fr}_1$		0.006 (1.25)		
$\hat{f}^{fr}_2$		0.018 (2.00)*		
$\hat{f}^{fr}_3$		0.003 (0.29)		
$\hat{f}^{it}_1$			0.001 (0.10)	
$\hat{f}^{it}_2$			0.063 (3.75)**	
$\hat{f}^{it}_3$			0.092 (8.01)**	
$\hat{f}^{sp}_1$				0.020 (1.92)*
$\hat{f}^{sp}_2$				0.001 (0.11)
$\hat{f}^{sp}_3$				0.028 (1.55)
R^2	0.297 [0.276]	0.440 [0.432]	0.233 [0.081]	0.094 [0.073]
Obs	408	408	408	408

Note: This table reports the estimation results of the regression of the DCC covariance between bond and stock market returns in the same country on the global and country-specific factors, see Eq. (8). The coefficients reported were multiplied by 10^3 for readability. Sample of 408 observations from 2004w1 to 2011w45. In parenthesis are the t-statistic of the coefficient. In square brackets is the R-squared of the regression with only global factors.

** Significant at 1%.

* Significant at 5%.

Table 6
Stock market returns variance (using 1st stage DCC model).

	Germany	France	Italy	Spain
Global				
f_2^{us}	0.410 (7.52)**	0.329 (8.68)**	0.354 (9.85)**	0.330 (8.16)**
f_2^{us}	0.325 (5.99)**	0.287 (7.48)**	0.369 (11.41)**	0.364 (9.32)**
f_3^{us}	0.454 (6.30)**	0.349 (6.74)**	0.337 (6.55)**	0.316 (5.79)**
Country				
$\hat{f}_1^{de}$	0.078 (1.96)			
$\hat{f}_2^{de}$	0.260 (2.63)**			
$\hat{f}_1^{fr}$		0.050 (2.19)*		
$\hat{f}_2^{fr}$		0.042 (1.12)		
$\hat{f}_3^{fr}$		0.024 (0.45)		
$\hat{f}_1^{it}$			0.022 (0.51)	
$\hat{f}_2^{it}$			0.068 (1.25)	
$\hat{f}_3^{it}$			0.008 (0.19)	
$\hat{f}_1^{sp}$				0.008 (0.18)
$\hat{f}_2^{sp}$				0.076 (1.88)
$\hat{f}_3^{sp}$				0.149 (2.11)*
R^2	0.539 [0.520]	0.571 [0.566]	0.566 [0.564]	0.551 [0.537]
Obs	408	408	408	408

Note: This table reports the estimation results of the regression of the variance of stock market returns in a given country (Germany, France, Italy, Spain) on the global and orthogonalized country-specific factors [see Eq. (9)]. The coefficients reported were multiplied by 10^3 for readability. The sample consists of 408 observations from 2004w1 to 2011w45. In parentheses are the t-statistic of the coefficient using robust standard errors. In brackets are the R-squared of the regression with only global factors.
** Means significant at 1%.
* Means significant at 5%.

Table 7
Bond market returns variance (using 1st stage DCC model).

	Germany	France	Italy	Spain
Global				
f_2^{us}	0.169 (5.01)**	0.073 (5.96)**	0.030 (1.77)	0.046 (1.76)
f_2^{us}	0.370 (9.27)**	0.097 (7.12)**	0.101 (4.46)**	0.239 (6.18)**
f_3^{us}	0.201 (3.62)**	0.089 (4.85)**	0.040 (0.99)	0.051 (0.89)
Country				
$\hat{f}_1^{de}$	0.088 (1.97)*			
$\hat{f}_2^{de}$	0.214 (2.49)*			
$\hat{f}_1^{fr}$		0.036 (2.11)*		
$\hat{f}_2^{fr}$		0.065 (2.92)**		
$\hat{f}_3^{fr}$		0.057 (1.80)		
$\hat{f}_1^{it}$			0.065 (0.89)	
$\hat{f}_2^{it}$			0.009 (0.20)	
$\hat{f}_3^{it}$			0.310 (3.33)**	
$\hat{f}_1^{sp}$				0.089 (1.08)
$\hat{f}_2^{sp}$				0.113 (2.11)*
$\hat{f}_3^{sp}$				0.095 (1.06)
R^2	0.262 [0.243]	0.245 [0.216]	0.227 [0.051]	0.115 [0.097]
Obs	408	408	408	408

Note: This table reports the estimation results of the regression of the variance of bond market returns in a given country (Germany, France, Italy, Spain) on the global and orthogonalized country-specific factors [see Eq. (9)]. The coefficients reported were multiplied by 10^3 for readability. The sample consists of 408 observations from 2004w1 to 2011w45. In parentheses are the t-statistic of the coefficient using robust standard errors. In brackets are the R-squared of the regression with only global factors.
** Means significant at 1%.
* Means significant at 5%.

5. Robustness and additional results

5.1. Nonparametric covariances

We use as a robustness check a nonparametric measure of covariance, given in Eq. (4), with $m = 20$ weeks rolling window. The results are shown in Appendix D.1. The R squared remains similar to that in the benchmark regressions in the previous section: around 0.60 for the stock market and 0.25 for the sovereign bond market. The coefficients of the global factor are statistically significant in both markets, with the three global factor always positive, confirming that the worsening of economic activity in the United States raises the covariance between asset returns in Europe.

Concerning the comovement between stock and bond returns within the same European country, Appendix D.4 shows that the results obtained in Section 4.2.1 are quite robust when we use the nonparametric measure of covariance instead of parametric one, albeit weaker for Italy and Spain.

5.2. Predicting correlations

As an alternative measure of comovement, common in the literature, we use the correlation coefficient. We run the following regressions:

$$Correl_{t+1}\left(r^k_{i,t+1}, r^k_{j,t+1}\right) \quad \nu + \phi' \mathbf{f}^{us}_t + \lambda' \hat{\mathbf{f}}^i_t + \pi' \hat{\mathbf{f}}^j_t + u_{t+1}, \tag{10}$$

where $Correl_{t+1}(r^k_{i,t+1}, r^k_{j,t+1})$ is the correlation between the asset returns in country i and in country j. The estimation results for both the parametric (DCC) and nonparametric (Eq. (5)) correlations' measures are presented in Appendices D.2 and D.3, respectively.

For the stock market correlation, the coefficients of the global factors have the same positive sign as that of the covariance. A recession in the United States raises the correlation between European stocks. The specific factors have heterogeneous effects per country pair. The R squared varies between 0.10 and 0.36. The results are robust to the use of the nonparametric measure of correlation in Eq. (5).

For the bonds market correlation, the third factor has a positive and statistically significant coefficient while the second factor has a negative coefficient. While a worsening of economic condition in the United States is more associated with manufacturing and investment raises the correlation in Europe, a worsening of conditions associated with lending, construction, and property lowers the correlation. The first global factor also has a positive effect but is generally statistically insignificant. Furthermore, we find that specific factors contribute to explaining the correlations between bond market returns, and the sign of their effect changes depending on the countries under consideration. These results are confirmed globally when we use the nonparametric approach. The R squared for bond markets varies between 0.16 and 0.28.

Regarding the comovement between stock and bond returns within the same European country, we re estimated Eq. (8) after replacing the covariance by the correlation measure. The results using both parametric and non parametric correlations' measures are reported in Appendix D.4. The results using correlation measure are somehow different from those we obtained using covariance measure (see Section 4.2.1). However, when we only focus on the statistically significant coefficients, we find that the results using covariance and correlation are quite similar, thus the economic interpretation of the effects remained the same as in Section 4.2.1.

5.3. Impact of European factors

Here we examine the impact of regional (European) factors on cross country stock and bond comovements. European factors were estimated in a similar way as country specific factors, but using joint information on European countries for the same period of time. We use the series for all European countries and extract three factors. We consider the following regression where the country specific factors in Eq. (8) where replaced by the European factors:

$$Cov_{t+1}\left(r^k_{i,t+1}, r^k_{j,t+1}\right) \quad \nu + \phi' \mathbf{f}^{us}_t + \lambda' \hat{\mathbf{f}}^{eu}_t + \varepsilon_{t+1}, \tag{11}$$

where $Cov_{t+1}(r^k_{i,t+1}, r^k_{j,t+1})$ is the covariance between asset returns in countries i and j, for $k =$ stock return, bond return; f^{us}_t is the vector of global factors; and $\hat{f}^{eu}_t$ is the vector of regional factors. We did not include country specific factors into the regression in Eq. (11) to avoid multicollinearity problems since the regional factors were constructed using information from specific countries. The results are provided in Appendix D.5.

Global factors are the dominant factors for the European stock and bond comovements, respectively. The new regional factors do not add much to the predictive content of global factors for predicting the covariances between European stock and bond returns. The sign of the impact of global factors on both stock and bond market comovements is still positive in general, thus the economic interpretation of this impact is still the same as in Section 4.1. Regarding the regional factors, only the third factor affects the European stock and bond comovements, and it has a positive effect on stock comovements and negative one (except for the pair Italy Spain) on bond comovements.

5.4. *Impact of observed and latent macro factors*

In this subsection we provide additional results that show the impact of macroeconomic based risk factors on the cross country stock market and bond market covariances and compare them with those based on *Google* data. The data used for this exercise is a monthly data, because most of the macro variables are observed at least at monthly frequency. We extract three macro based risk factors from 20 US macroeconomic series that were previously used in Section 3.3, using principle component analysis. As an alternative, we also looked at the impact of observed macro variables (unemployment rate, consumer price index and industrial production). The results are reported in Appendix D.6.

The US macro based risk factors provide significant information for the cross country stock market covariance. Their impact is statistically significant at 1% significance level. The R squared is quite high and varies between 0.56 and 0.69, although it is lower than the factors extracted from *Google* data. Notice that several of the *Google* factors are now not significant, because of the reduction of the number of observations. If we consider the macro variables directly, they have a statistically significant effect on the comovement among European stock markets. However, the sign of this effect varies: unemployment rate and industrial production have a negative impact, whereas consumer price index has a positive impact on the stock market covariance. The R squared varies between 0.36 and 0.45, which indicates that these variables are informative about the comovement but less than both the *Google* and macro based risk factors.

The macro factors also have an effect on the bond market covariance, but it is economically (magnitude of the coefficients) and statistically less significant compared to the one obtained for stock market covariance, which is consistent with the results with *Google* data. The decreases in economic significance are confirmed by a lower R squared that varies between 0.19 and 0.50. The signs of the coefficients are quite similar to those obtained for stock market covariance, except for the pairs Germany Italy and Germany Spain.

6. Implications for international risk diversification

We now turn to the implications of our previous results for international risk diversification. We construct international asset portfolios using *Google* search based factors and evaluate their performance. We use a novel approach that consists of modeling port folio weights directly. Portfolio weights modeling was proposed by Brandt and Santa Clara (2006) to overcome the classical problems of the mean variance portfolio. Brandt et al. (2009) model portfolio weights as a function of predetermined economic variables. They consider that all assets in a given portfolio are related to common variables through different functions (coefficients). Their method ology is computationally simple, produces sensible weights, and performs better. Bouaddi and Taamouti (2013) extend this approach to model the weights as a function of *latent factors* that summarize the information in a large number of economic variables representing different sectors of the economy using a factor model with principal component analysis as in Bai and Ng (2002) and Stock and Watson (2002a, 2002b). In our setting, we assume that the weights are functions of the global factors.

Consider a portfolio constructed using stocks or bonds separately from n countries, with the vector of weights at time t given by $\omega_t=(\omega_{1,t},\ldots,\omega_{n,t})^T$, with $\sum_j \omega_{j,t} = 1$. We modify the weight function in Bouaddi and Taamouti (2013) and assume that it is a linear function of the *global factors*. Thus, we solve the conditional portfolio choice problem by parameterizing portfolio weights as follows:

$$\omega_{j,t} = \vartheta_{j,0} + \vartheta'_{j,1} f^{us}_{1,t} + \vartheta'_{j,2} f^{us}_{2,t} + \vartheta'_{j,3} f^{us}_{3,t}, j = DE, FR, SP, \tag{12}$$

where $\vartheta_{j,1}$, $\vartheta_{j,2}$ and $\vartheta_{j,3}$ are the parameters measuring the response of the weight in country j to the corresponding *global factor*. The matrix ϑ of the above coefficients is chosen optimally by maximizing the investor's average utility

$$\hat{\vartheta} = \text{Arg} \max_{\vartheta} \left\{ \frac{1}{T} \sum_{t=1}^{T-1} u\left(\omega_t^T r_{t+1}\right) \right\}, \tag{13}$$

for a given utility function $u(.)$, where r_{t+1} is the vector of returns of the n assets (stocks or bonds). While the specification of $u(.)$ is a matter of choice, the power utility function of the form

$$u\left(\omega_t^T r_{t+1}\right) = \frac{\left(1+\omega_t^T r_{t+1}\right)^{1-\zeta}}{1-\zeta}$$

gives great flexibility in the empirical analysis as it takes into account not only the mean and variance, but also higher order mo ments such as skewness and kurtosis, without introducing additional parameters. The portfolios selected under the constant rel ative risk aversion utility function maximize the mean and skewness and minimize the variance of portfolio returns [see Brandt et al. (2009, page 3417)]. Following the literature, we take the risk aversion, ζ, as equal to 5 and 8. To evaluate the performance of our portfolios, we use a leading performance measure, i.e., the Sharpe ratio, given by

$$SR(\omega_t) = \frac{\mu(\omega_t)}{\sigma(\omega_t)},$$

Table 8
Portfolio comparison.

Portfolio	Stock market				Bond MARKET			
	Mean	St. Dev.	SR	FT	Mean	St. Dev.	SR	FT
In-sample								
Equally weighted	0.0%	0.055	0.000	0.755	0.0%	0.050	0.009	0.904
Risk aversion = 5								
Constant weights	1.6%	0.060	0.268	1.053	1.1%	0.070	0.152	1.313
Google (weekly)	5.3%	0.121	0.435	1.455	4.6%	0.169	0.275	2.528
Google (monthly)	4.2%	0.101	0.418	1.568	2.7%	0.109	0.246	1.611
Risk aversion = 8								
Constant weights	0.9%	0.053	0.170	1.139	0.6%	0.057	0.107	1.058
Google (weekly)	3.4%	0.088	0.393	1.189	2.9%	0.110	0.266	2.056
Google (monthly)	2.5%	0.070	0.362	1.414	1.6%	0.075	0.213	1.596
Out-of-sample (1 year)								
Equally weighted	1.9%	0.068	0.283	0.048	0.6%	0.067	0.108	0.642
Risk aversion = 5								
Constant weights	0.1%	0.072	0.008	0.489	2.0%	0.087	0.228	0.732
Google (weekly)	11.8%	0.264	0.447	1.215	1.7%	0.547	0.031	0.551
Google (monthly)	3.2%	0.197	0.164	0.621	2.9%	0.393	0.074	0.303
Risk aversion = 8								
Constant weights	0.6%	0.070	0.080	0.394	2.1%	0.077	0.279	0.926
Google (weekly)	7.1%	0.198	0.360	2.099	0.2%	0.328	0.005	0.508
Google (monthly)	3.1%	0.133	0.231	0.933	2.9%	0.127	0.230	1.399

Note: The table summarizes the portfolio performance at a monthly frequency. The portfolios are constructed based on the weight function in Eq. (12) and the coefficients in Eq. (13), estimated using the generalized method of moments. The instruments used consist of four lags of $r_{j,t+1}, r_{j,t+1}f^{us}_{1,t}, r_{j,t+1}f^{us}_{2,t}$, and $r_{j,t+1}f^{us}_{3,t}$. The constant weights portfolios only estimate the constant term $\vartheta_{j,0}$. Two portfolios are constructed using *Google* search data at weekly and monthly frequencies (reported statistics are for monthly portfolio results). For the weekly estimation, the sample has 402 observations. For the monthly portfolio, the sample has 93 observations from 2004m2 to 2011m10. For the out-of sample portfolio, we show the summary of the portfolio for the last year of the sample (52 weeks or 12 months). We estimate Eq. (12) up to week (month) t and compute the weights for the following week (month). SR stands for Sharpe ratio and FT stands for the Farinelli and Tibiletti (2008) ratio defined in Eq. (14) for p = q = 1.

where $\mu_p(\omega)$ and $\sigma_p(\omega)$ are the mean and standard deviation of portfolio returns, respectively. Higher values of the Sharpe ratio indicate good performance. However, if portfolio return distributions are skewed, then a favorable shift in probability mass may result in a lower Sharpe ratio. Since the latter quantifies and rewards risk through two sided type measures, positive and negative deviations from the benchmark are weighted in the same manner. Farinelli and Tibiletti (2008) propose one sided measures of performance [hereafter FT ratios] that capture two types of asymmetrical information: (1) "good" volatility (above the bench mark) and "bad" volatility (below the benchmark), and (2) asymmetrical preference to bet on potential high stakes and the aver sion against possible huge losses. Thus, we evaluate the performance of previous portfolios using also the following FT ratios:

$$FT(\omega_t) \quad \frac{\left(E\left[\left|r_{p,t}(\omega_t)-b\right| \, |r_{p,t}(\omega_t) > b\right]^p\right)^{\frac{1}{p}}}{\left(E\left[\left|r_{p,t}(\omega_t)-b\right| \, |r_{p,t}(\omega_t) < b\right]^q\right)^{\frac{1}{q}}}, \tag{14}$$

where $r_{p,t}(\omega)$ denotes the portfolio returns, b is a benchmark threshold, and p and q are positive constants. In our empirical anal ysis we take b equal to zero, but other values can be considered. The FT ratios can be viewed as general risk reward indexes suit able to compare skewed returns with respect to a benchmark. For some particular values of p and q, the FT ratios correspond to some known indexes. For $p=q=1$, we have the Omega index proposed by Cascon, Keating, and Shadwick (2013) and for $p=1$ and $q=2$ we get the Upside Potential index suggested by Sortino, van der Meer, and Plantinga (1999). The analysis covers the four European countries described in Section 3 and is done separately for stocks and bonds.

We build two portfolios based on *Google* search data. The first portfolio is constructed as a function of the global factors of the pre vious week by allowing weekly adjustments. In the second portfolio, we average the information over the month and only allow monthly adjustments, as a function of information of the previous month. We distinguish these two portfolios to understand whether the gains come from the information itself or from its frequency. We compare the portfolios to an equally weighted portfolio and one with constant weights, estimated from Eq. (12) with only the constant terms. We do an in sample exercise and an out of sample ex ercise. In the in sample exercise, the portfolio weights are estimated using the whole sample. The out of sample exercise is for the last year of the sample (52 weeks or 12 months). We estimate the model up to a given week (month) and use the estimates to determine the portfolio weights in the following week (month). The average monthly portfolio returns, their standard deviations, and the Sharpe and FT (for $p=q=1$) ratios are presented in Table 8. Additional portfolio performance results that correspond to different values of parameters p and q in the FT ratio formula in Eq. (14) are reported in Appendix E.3.

The portfolio based on *Google* search factors generally outperforms the others, having higher returns and Sharpe and FT ratios, especially for a stock market with a low risk aversion coefficient. It is not surprising given that the global factors explained the covariance in the stock market more than they did the covariance in the bond market. Although there are gains from having the monthly portfolio, the weekly portfolio generally performs better. The equally weighted and constant weights portfolios, es pecially in the out of sample exercise, both have a negative return, and so does the portfolio constructed at a monthly frequency. The weekly portfolio constructed using the global factors has high and positive returns, particularly on the stock market. As the crisis unfolded quickly, having a portfolio with weekly adjustments based on consistent data proves a crucial element for good performance.

Appendix E.1 reports the estimated coefficients of the weights of the weekly portfolio. The three global factors have significant effects on the weights of stocks and bonds of most countries. However, the sign pattern is less apparent and depends on the coun tries. Appendix E.2 displays the estimated weights of the factor based portfolio for the two markets and the four countries. The portfolio weights are time varying and more volatile after the Eurozone crisis of 2008. Overall, the optimal portfolio that uses *Google* search factors does not reflect any unreasonably extreme bets.

To provide an economic interpretation of the factor based portfolio weights, Appendix E.2 reports the results of marginal re gressions of the country weights for the two markets on three US macroeconomic variables: unemployment rate in first differ ences, and consumer price index and industrial production index in growth rates. The three macroeconomic variables have, in general, statistically significant effects on the weights, particularly the industrial production index. For the weekly portfolio, lower industrial production raises the weight on German and Italian bonds and stocks, relative to the French and Spanish ones.

It is not surprising that the portfolios in which the weights depend on Google search factors maximize mean return and reduce investment uncertainty (variance). As we found before in Section 3.3, these factors are indicators of relevant economic activities such as unemployment, prices, and output. Flannery and Protopapadakis (2002) examined the impact of 17 macroeconomic var iables on the mean and volatility of stock returns and found that most of the above variables affect the mean and/or variance of stock returns [see also Benzoni, Collin Dufresne, and Goldstein (2007)and Rangvid (2006) among others]. The inflation tends to cause stock prices to go down because the effective rate of return from current dividends and earnings must increase for investors to be interested. Furthermore, Katzur and Spierdijk (2013) show that the relationship between stock returns and inflation has substantial influence on optimal asset allocation. Finally, Ludvigson and Ng (2009) among others found that macroeconomic fun damentals such as output and unemployment have important forecasting power for future conditional mean of bond returns.

7. Conclusion

We characterize stock and bond comovements in a broad class of affine general equilibrium models. In particular, we show that the covariances between stock and bond markets are linear functions of risk factors, which implies that if measures of covari ances and risk factors are available, simple econometric techniques can be used to predict stock and bond comovements.

A novel approach is used to measure risk factors based on *Google* search, which can produce economic activity data at a high frequency. The empirical analysis focuses on the Euro Area, before and after the Eurozone crisis. It uses weekly data and the DCC model to measure the covariances in the Euro Area and uses nonparametric measures of covariances to check the robustness. The results indicate that Google search based factors contain useful information and are able to predict international stock and bond comovements.

We find that most of the variation in the covariance between European stock market returns is driven by global factors, and more concretely, by US economic conditions. Any dimension of a recession in the United States raises the covariance between European stocks. The sovereign bond market is less driven by global factors, with country specific factors playing a larger role.

We also find that there are substantial gains for investors of using these type of data. Portfolios with time varying weights as a function of the global factors outperform the equally weighted portfolios and other constantly weighted portfolios, particularly out of sample.

A more general conclusion of the study is that the data provided by *Google* search has a huge potential for use in finance. While we restrict ourselves to only 10 indexes, *Google Trends* supplies hundreds of indexes regarding several sectors of economic activity. The data readily available at a weekly frequency for different countries offers great prospects for economists studying the connection between the real economy and finance, as well as for investors focusing on firm, sector, or country finance.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.iref.2016.03.005.

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